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**The Best of Both Worlds:  
Designing Complex Experiments in the JMP-SAS Environment**  
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**ABSTRACT**

Complexity, and supply chains that may expand across the globe, requires us to design experiments that must take into account: 1) the multi-step nature of manufacturing processes, 2) the large number of factors involved, 3) the different sizes of experimental units, 4) the restrictions in randomization that occur, and 5) the constraints in the number of experiments that can be run. Designing experiments for these situations can challenge many design of experiments software packages. However, the JMP-SAS integration now allows us to take advantage not only of the flexibility and power of the Custom Designer, but also of new capabilities of SAS 9.2 PROC FACTEX to design experiments for multi-step processes. The gamut of manufacturing situations that can now be handled with JMP-SAS will be illustrated using the Custom Designer to design an experiment for a complex manufacturing situation involving a hard-to-vary factor, 9 process factors, and 8 mixture factors; and demonstrating how a JMP-SAS application can be used to design experiments for 3, 4, and 5 step processes.

**1. INTRODUCTION**

The realities of complex manufacturing situations present us with challenges when designing experiments because we have to take into account:

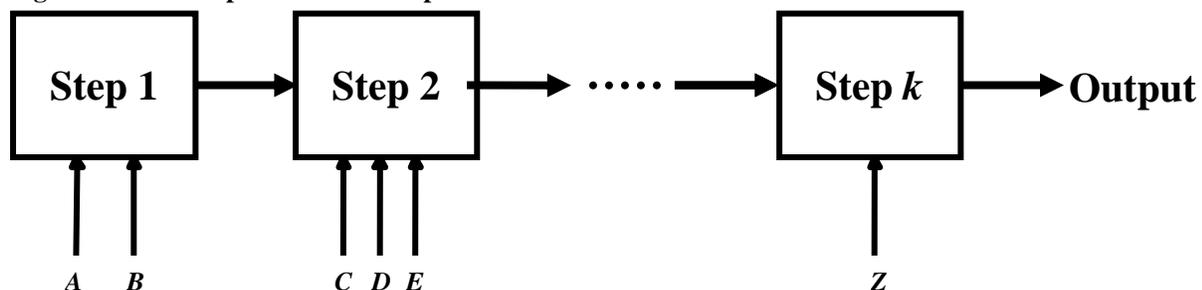
1. The multi-step nature of manufacturing processes that involve process steps at different plants that can be located across the street, or across the globe.
2. The large number, and different types, of factors involved, including process and mixture factors.
3. The different sizes of experimental units that can result as raw materials and intermediate products pass from one manufacturing step to the next.
4. The restrictions in randomization that occur which makes it very difficult, or impossible, to fully randomize all the experimental runs as required by good experimental design practices.
5. The constraints in the number of experiments that can be run. With a large number of factors an experiment can get (very) large making it next to impossible to run a full factorial.

Fortunately for us recent developments in experimental design, and their availability in JMP and SAS, make it easier for us to generate experimental designs for these situations. We start by discussing multi-step processes and split-plot designs, and give examples of designing complex experiments using the Custom Designer in JMP, as well as PROC FACTEX in SAS, using the JMP-SAS integration.

**2. MULTI-STEP PROCESSES AND SPLIT-PLOTS DESIGNS**

A multi-step process is one in which different manufacturing steps are carried in sequence either in the same location, but more often, in different plants, or even across the world. At each process step different process parameters can be changed as shown in Figure 1

**Figure 1. An Example of a Multi-Step Process**



One quickly realizes that the number of experimental factors can become quite large, and the numbers of experiments required can be prohibitive. For example, a full factorial for a 4-Step process with 3 2-level factors at

each process step requires  $2^{12} = 4096$  runs. In these situations, therefore, a full factorial experiment is out of the question. In some cases, in order to manage this complexity, experiments are designed for each process step separately, but this usually leads to sub-optimization of the complete multi-step system because the interactions between the process steps are not included. What is needed is a holistic approach that takes into account each process step and its group of factors, and the interactions between all the factors in the multi-step process. Understanding these interactions is critical for the global optimization of the multi-step process.

Multi-step processes usually give rise to split-plot (split-unit) design structures. In general, split-plot designs occur primarily in two situations (see Ramírez (2004)):

1. There is a *restriction in randomization* for an experimental factor.  
For example, running all treatment combinations associated with “low” temperatures followed by all treatment combinations associated with “high” temperatures.
2. There are *different sizes of experimental units*.  
For example, an experimental factor, F1, may be applied to a 500 meters roll of material, while another factor, F2, can be applied to a 2509 meters piece of the roll. The Roll was “split” into two 250-meter sections for the second experimental factor F2.

The larger the number of process steps, the larger the number of “splits” in the experimental structure.

### 3. DESIGNING EXPERIMENTS FOR MULTI-STEP PROCESSES

The noted engineer and physicist Theodore Von Karman remarked, “Scientists discover the world that exists; Engineers create the world that never was.” Designed experiments are an efficient way of learning about these worlds. The main goal of a designed experiment is to generate *signals* that can help us answer the questions of interest, about our processes or products, in the presence of natural random variation or *noise*.

As we discussed before the nature of multi-step processes makes the use of full factorial designs unrealistic. We need ways of designing experiments with enough runs to estimate the signals that will allow us to answer our uncertainties, and allow us to generate estimates of noise that can be used to construct the appropriate signal-to-noise ratios to evaluate the strength of our signals. In addition, restrictions in randomization or different sizes of experimental units, the constraints on the number of resources available, along with the different factors types (process and mixture factors) that we may encounter, require experiments that also take into account the split-plot structure induced by multi-step processes, and these different types of factors.

#### Experimental Factors

Experimental factors are the signal generators in the sense that we expect our responses to change when we manipulate them. Two types of experimental factors are:

- Process factors: process “knobs” that can be changed to induce a signal in our responses.
- Mixture factors: they are *ingredients* in a “formulation”, in the sense that their combined contribution must add to a 100%.

Two main approaches are possible when designing experiments for complex multi-step processes: 1) we can use fractional factorial split-plot designs, or 2) we can specify a model, along with an optimality criterion, to obtain an optimal design. Optimal designs also allow us to combine process and mixture factors in a design.

#### 3.1 FRACTIONAL FACTORIAL SPLIT-PLOTS (FFS<sup>K</sup>P)

Fractional factorial designs are a very efficient way to run experiments subject to constraints on the number of observations. The idea of constructing fractional factorials to take into account the split-plot confounding is not new. Kempthorne (1952) called these types of designs fractional factorial split-plot, and Addelman (1964) provided a table of factorial plans with split-plot confounding for different number of Whole-Plot and Split-Plot factors. However, in recent years there has been a wave of research on fractional factorial split-plots (FFSP). Huang et al (1998), and Bingham and Sitter (1999, 2001) have applied the concept of *minimum aberration* (Fries and Hunter (1980)) to split-plot designs, giving comprehensive tables for small to moderately sized minimum aberration split-plot designs, while Kulahci et al (2006) have discussed alternative criteria to minimum aberration for designing FFSP.

Useful catalogs of FFSP have appeared in the pages of various journals. For example, Huang, Chen, and Voelkel (1998) give a catalog of minimum aberration fractional split-plot designs. In this era of great computing power we do not need to be limited by looking at tables for a design, we can let the computer find an appropriate design given design and model constraints. In SAS® Version 9.2 PROC FACTEX enables us to construct custom FFSP designs for situations with *multi-step* processes, or with more complex restrictions in randomization, and multiple sizes of experimental units. The intuitive syntax allows multiple specifications of wholeplots and subplots, making it possible to cover a wide array of situations (See also, Ramírez and Tobias (2007)).

### 3.2 OPTIMAL DESIGNS

Optimal, or optimum, designs are based on “the model relating the responses to the experimental factors” (Atkinson, et al. (2007)). The model relating the responses to the experimental factors needs to be specified in terms of the terms we want to estimate with the data. In other words, we need to specify which main effects, interactions (two-factor, three-factor, etc.), and higher order terms that we want to estimate. For a screening type experiment we may only specify the main effects. For multi-step process we also want to be able to estimate two-factor interactions within a process step, and between process steps.

Optimal designs are generated by means of computer algorithms using the specified model and a criterion to be optimized. Criteria are classified into information-based or distance based. D-Optimality is the most commonly used information-based criterion for generating optimal designs. D-Optimality seeks to maximize the determinant of the information matrix, which the reciprocal of the variance-covariance matrix of the parameters in the specified model. The higher the D-optimality the more precision we will have in estimating the model parameters. Another criterion, available in JMP, is I-Optimality, which seeks to minimize the average prediction variance.

Optimal designs are particularly useful when classical factorial designs do not apply. These situations include, for example, designs where factors have different number of levels, or complex situations involving process and mixture factors.

## 4. DESIGNING COMPLEX MULTI-STEP EXPERIMENTS IN THE JMP ENVIRONMENT

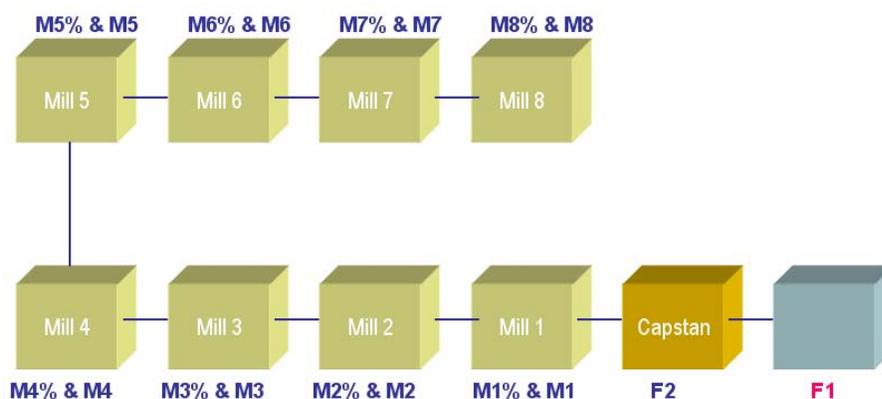
In JMP 8 users can take advantage of the optimality criteria approach to design experiments for a great variety of experimental situations including 2-Step and 3-Step processes, and process-mixture experiments. For those situations where the multi-step process has more than three steps, or if one wants a fractional factorial design for a 2-Step or 3-Step process, PROC FACTEX in SAS 9.2 allows the user to design fractional factorial split-plots for virtually any number of process steps.

To show the power and flexibility of the Custom Designer in JMP we give two examples of multi-step processes.

### 4.1 A COMPLEX EXPERIMENT WITH 10 PROCESS FACTORS AND 8 MIXTURE FACTORS

A particular milling operation consists of 8 mills as shown in Figure 2. A 2-level process factor, F2, controls the way the product travels through the 8 mills and, at each mill, a 2-level process factor (M1-M8), and a mixture factor (M1%-M8%) can be changed to alter the quality of the product. The 8 mixture factors are proportions that need to add to 100%. At the start of the process a 3-level hard-to-vary factor, F1, determines which type of product the milling process will process.

Figure 2. Milling Operation with 18 Factors



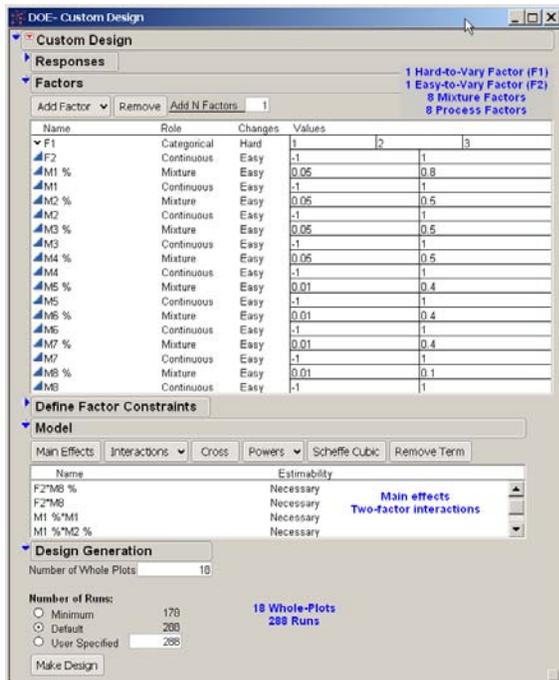
The hard-to-vary factor F1 induces a split-plot design structure with F1 as the whole-plot factor, and factors F2, M1-M8, M1%-M8% as the sub-plot factors. In order to design an experiment for this milling process we need to take into account:

1. The split-plot structure (factor F1)
2. The combination of process and mixture factors
3. The mixed level design with one 3-level factor, nine 2-level factors, and eight mixture factors.
4. The availability of resources. A full factorial will require  $3 \times 2^9 \times 120 = 184,320$  runs.
  - This includes 120-run full cubic simplex lattice design for the mixture factors

An experiment with 100,000+ runs is out of the question. How can we design an experiment that takes into account all of our constraints? A few years ago, designing an experiment like this would have been either impossible to design, or would have require a specialized code. The Custom Design platform (**DOE > Custom Design**) in JMP provides us with the flexibility and power to handle many types of design including this one.

Figure 3 shows the Custom Design dialog window that allows us to specify the structure of our design. Factor F1 has a *Categorical* role, is *Hard* to change, and has 3 levels, while Factor F2 is *Continuous*, *Easy* to change, and has 2 levels. The milling process factors, M1-M8, are *Easy* to change and have 2 levels each, and the mixture factors, M1%-M8%, are also *Easy* to change, the levels representing the ranges for a given proportion. For example, M1% can vary between 5% and 80%, but M6% can only vary between 1% and 40%.

**Figure 3. JMP Custom Design Input Window Dialog**



The trick is to find a split-plot design, preserving the restrictions in randomization, for which the levels of the mixture combinations add to 100%, and that allows us to estimate all the main effects, and the 153 two-factor interactions in a reasonable number of runs.

At the bottom of Figure 3 you can see that the Custom Designer will try to find a design with 18 whole-plots, i.e., there will be 18 runs of the three levels of the hard-to-vary factor F1, and within each of these runs will have runs for the other 17 factors in the milling operation. The default number of runs that the Custom Designer suggests is **only** 288 runs, which is only 0.25% of the full factorial. One thing to remember is that this design will take some time to find; i.e., we need to let the Custom Designer run for a while to find an optimal design. A partial view of the resulting design is shown in Figure 4 (mixture values were rounded to 2 decimal places).

The design in Figure 4 is an efficient and balanced design in the sense that each of the 3 levels of the hard-to-vary factor is repeated 6 times for a total of 18 whole-plots, and within each of these 18 whole plots we have 16 unique runs of the other 17 factors. Not only that, with 288 runs we have enough degrees-of-freedom to estimate all the main effects, and the 153 two-factor interactions.

Figure 4. Custom Design Experiment (Partial View) for Milling Operation with 18 Factors

4.2 A 3-STEP PROCESS EXAMPLE (SPLIT-PLOT)

Consider a situation where a process is run in three steps. In Step 1 there is one 2-level factor Z. In Step 2 the material coming from Step 1 is processed according to seven 2-level process factors (A, B, C, D, E, F, G). Finally, in Step 3 the product reaches its final form by means of eight 2-level process factors (P, Q, R, S, T, U, V, W). This 3-step process gives rise to a split-split-plot structure  $2^1 \times 2^7 \times 2^8$ . We would like to design an experiment to estimate all the 16 main effects Z, A, B, C, D, E, F, G, P, Q, R, S, T, U, V, W and, if possible, all the 120 2-factor interactions between the 16 factors. Our goal is to be able to understand how the 3 process steps interact with each other and for this we need to be able to estimate all the interactions between Z and A, B, C, D, E, F, G and P, Q, R, S, T, U, V, W.

Figure 5. A 3-Step Process with 16 Factors:  $2^1 \times 2^7 \times 2^8$  Experiment

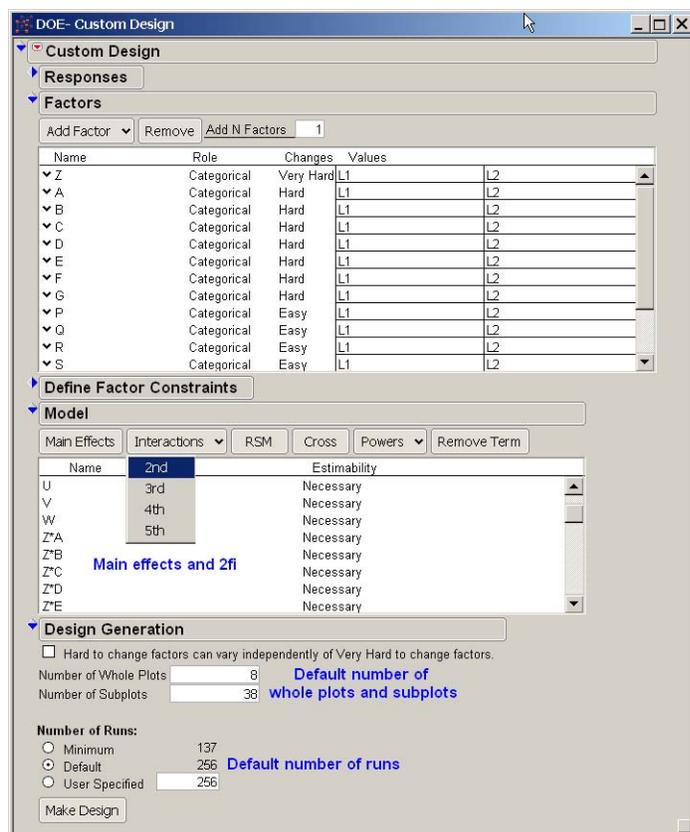


The full factorial will require  $2^1 \times 2^7 \times 2^8 = 65,536$  runs, which is an unreasonable number from the practical point of view. As you can see, we need to find a design that satisfies the 3 restrictions in randomization, that allows the estimation of the 16 main effects and, if possible, all the 120 2-factor interactions, and does it in a reasonable number of runs.

Once again, the Custom Design platform (DOE > Custom Design) in JMP can be used to design a split-split-plot type experiment to estimate all the main effects, and all the two factor interactions. Step 1 factor Z is a *Very Hard* to change factor; it defines the whole-plot. Step 2 factors A, B, C, D, E, F, G are *Hard* to change factors; they define the Split-Plot. While Step 3 factors P, Q, R, S, T, U, V, W are *Easy* to change factors; they define the Split-Split-Plot. These three steps define 3 randomizations: 1) in Step 1 we randomize the levels of factor Z, 2) in Step 2 we randomized the runs corresponding to factors A, B, C, D, E, F, G, and 3) in Step 3 we randomized the runs corresponding to factors P, Q, R, S, T, U, V, W.

Figure 6 below shows the inputs to the “Custom Designer”. The 3 restrictions in randomization are specified in the column Changes of the Factors dialog box. Note Z has “Very Hard”; A, B, C, D, E, F, G “Hard”, and P, Q, R, S, T, U, V, W “Easy”. By including two-factor interactions (Interactions > 2nd) in the Model dialog box we insure that all of the 120 two-factors are estimable (Estimability > Necessary).

Figure 6. Custom Design Inputs for  $2^1 \times 2^7 \times 2^8$  Experiment with 8 Whole Plots and 38 Subplots.



The Custom Designer offers, by default, a design with 256 runs, in which all the two factor interactions are clear of confounding with main effects and other two factor interactions (this is because we included all the two-factor interactions in the model making their estimation “Necessary”). Also by default, this experiment has 8 Whole Plots or 8 runs of the Step-1 factor Z, and 38 Subplots, or 38 runs of the Step-2 factors A, B, C, D, E, F, G. When you click on “Make Design” JMP starts the search for the 256-run design that meets the giving specifications of “Very Hard”, “Hard”, and “Easy” to vary factors, and allows the estimation of all main effects and two-factor interactions. Note that the Custom Designer took over 35 minutes in an Intel® Core™ Duo CPU E6850 3GHz; 3GHz to generate this design.

## 5. DESIGNING COMPLEX MULTI-STEP PROCESSES EXPERIMENTS USING JMP-SAS INTEGRATION

With JMP version 7 a new era of integration between JMP and SAS was made possible. JMP has been able to read and write SAS data sets for many versions, but JMP was not able to connect or submit SAS code to PC SAS on the same machine, or connect and submit SAS code to a remote server. This meant that JMP users could not leverage the variety of data management or statistical features available in other SAS products.

At the same time, SAS could not take advantage of the JMP Scripting Language’s (JSL) ability to create dynamic user interfaces or JMP’s interactive graphics.

By developing integration between JMP and SAS allowing “point and click” users of JMP to query and retrieve data from a SAS server as well as execute SAS reports (SAS Stored Processes), new access to corporate data assets and canned reports were available to JMP users for the first time.

The integration also offers the SAS programmer the ability to package SAS code within JSL and deploy it to JMP users within the organization. This means that SAS programmers leveraging the statistical power of SAS/QC and the user experience of the JMP environment can add new features, like support for Fractional Factorial Split-Plot designs, to JMP.

We have developed JSL code for designing fractional factorial experiments for multi-step processes situations, to take advantage of the new features in PROC FACTEX in SAS/QC using a native JMP interface. These capabilities enhance the Custom Design capabilities available in JMP 8, since the Custom designer cannot design split-plot designs with more than 3 levels of splits. This gives the JMP user more design choices.

Below we give 3 examples of multi-step process situations to show the applicability of the techniques, as well as the ease of use on the JMP-SAS application.

### 5.1 A 3-STEP PROCESS EXAMPLE (SPLIT–SPLIT–PLOT)

In Section 4.2 we showed how JMP Custom Designer was able to generate a D-optimal design for the 3-Step process in Figure 5. This (default) 256-run design is unbalanced because the 8 whole plots and 38 subplots do not have the same size. There are 6 whole plots of size 5, and 2 whole plots of size 4, while for the 38 subplots we have 6 subplots of size 4, 24 subplots of size 7, and 8 subplots of size 8. This can make the running of the experiment difficult or impractical because the unbalanced distribution of whole plot and subplots induces an unbalanced number of experimental factors.

The number of whole plots and subplots dictate how the experiment needs to be conducted. The Step-1 factor has to be changed 7 times, there are 8 runs (whole plots) of this factor; while for the 7 factors in Step-2 we need to run 38 different combinations, the 38 subplots. This structure needs to be taken into account to make sure that it is feasible, in terms of time and resources, to conduct the experiment this way. In other words, a good experimental design should give us the ability to estimate the signals of interest, under the experimental constraints, and it should not add unnecessary complexities to the actual running of the experiment.

Another issue with this design is that although all the main effects and 2-factor interactions are clear from confounding with other 2-factor interactions, the main effects in this D-optimal design are confounded with (long) strings of 3-factor interactions. Given that we have 16 factors in this experiment, and due to the complexity of the manufacturing process, it is quite possible for some of the 560 3-factor interactions to have an effect. Therefore, in this situation, it is desirable to have a design where the main effects are not only clear from 2-factor but from 3-factor interactions as well.

### PROC FACTEX

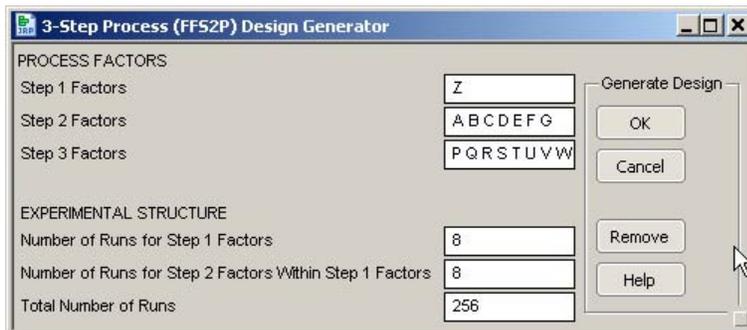
Fractional factorial designs are an alternative to optimal designs. We can take advantage of the new features in PROC FACTEX, SAS/QC version 9.2, view to generate a 256-run fractional factorial split-split-plot for the 3-Step process. The new features consist of the BLOCK UNIT=( ) option for describing the split-plot structure of the experiment, and the UNITEFFECT statement for specifying where effects of interest should be estimable within this scheme. We have developed code to allow the JMP user to generate fractional factorial split-plots via the JMP-SAS integration.

For the 3-Step process in Figure 5, we want to design an experiment in 256 runs (only 0.4% of the 65,536 runs for the full factorial), with 8 runs (whole-plots) of the Step 1 factor (Z), 8 runs (subplots) of the Step 2 factors (A, B, C, D, E, F, G) for each run of factor Z, and 4 runs (sub-subplots) of the Step 3 factors (, Q, R, S, T, U, V, W) for each Step 1 and Step 2 run. This is a balanced design in terms of the whole plots and subplots, making the running of the experiment easier than the design with 8 whole plots and 38 subplots generated by the Custom Designer.

Figure 7 shows the JMP interface for designing FFS<sup>2</sup>P experiments. We denote a 3-Step fractional factorial split-plot as FFS<sup>2</sup>P. The superscript 2 denotes the number of process steps after the first step, or the number of “splits”, hence the split-split-plot. In this window we input the process factors for each of the 3 steps, as well as the structure of the experiment in terms of the

1. Number of Runs for Step 1 Factors
2. Number of Runs for Step 2 Factors Within Step 1 Factors
3. Total Number of Runs

**Figure 7. JMP Interface for Designing 3-Step Process Experiments.**



When we click “OK” a connection to SAS is established, the information in Figure 7 is sent to PROC FACTEX in order to search for a design with those characteristics, and, if PROC FACTEX finds a suitable design, the results are sent

back to JMP. The SAS output that is returned to JMP consists of the design generators used in the construction of the fractional factorial split-plot, the alias structure for the main effects and 2-factor interactions, the word length pattern (aberration) of the design, and a JMP table with the FFS<sup>2</sup>P design. The JMP-SAS integration also gives us the ability to convert SAS output into a familiar JMP report where sections can be expanded or collapsed.

The (partial) alias structure in Figure 8 shows that all the main effects and 2-factor interactions are clear from confounding with 2-factor as desired. As an improvement to the JMP design, the Aberration section of the output in Figure 8 shows that the shortest words are of length 5 indicating that the fractional factorial split-split-plot design is of resolution 5. What does this mean? This means that the main effects are also clear from confounding with 3-factor interactions, which is a big plus in this situation.

**Figure 8. PROC FACTEX Output for FFS<sup>2</sup>P Experiment.**

Report: SAS Res... Report: SAS Res...

Fractional Factorial Split-Split-Plot  
The FACTEX Procedure

**Confounding Rules**

Factor

Confounding Rules

Z = [1]

A = [3]\*[6]

B = [2]\*[3]\*[4]

C = [4]

D = [1]\*[4]\*[6]

E = [2]\*[3]\*[5]\*[6]

F = [2]\*[3]\*[4]\*[6]

G = [3]\*[5]\*[6]

P = [1]\*[3]\*[5]\*[8]

Q = [2]\*[7]\*[8]

R = [1]\*[4]\*[6]\*[7]\*[8]

S = [2]\*[3]\*[6]\*[7]

T = [2]\*[3]\*[4]\*[5]\*[6]

U = [1]\*[5]\*[6]\*[7]

V = [3]\*[5]\*[7]\*[8]

W = [2]\*[6]\*[7]

**Aliasing**

**Aliasing Structure**

Z

A

B

C

D

E

F

G

P

Q

R

S

T

U

V

W

Z\*A

Z\*B

Z\*C

Z\*D

Z'E

Z'F

Z'G

Z'P

Z'Q

Z'R

Word Length Pattern

Word Length

1 2 3 4 5 6

Treatment factors 0 0 0 0 24 44

The JMP-SAS integration also allows the conversion of SAS datasets into ready-to-use JMP tables. Figure 9 shows the partial JMP table with the fractional factorial split-split-plot design. Apart from the factors columns, A, B, C, D, E, F, G, P, Q, R, S, T, U, V, W, there are two additional columns, Step1 and Step 2, that index the whole-plot and split-plot runs. The column Step 1 has values 1 through 8, and for each of the Step 1 values, column Step 2 has values 1 through 8. This gives a balanced design in which for each Step 1 whole-plot there are 8 subplots, for a total of 64 Step 2 subplots, and for each of the 64 whole-plot x subplot (Step1 x Step 2) combinations there are 4 Step 3 subplots for a total of 256 runs ( $8 \times 8 \times 4 = 256$ ).

Figure 9. Partial JMP Table with FFS<sup>2</sup>PDesign for 3-Step Process Example.

	Step1	Z	Step2	A	B	C	D	E	F	G	P	Q	R	S
1	1	-1	1	1	-1	-1	-1	1	1	-1	1	-1	-1	1
2	1	-1	1	1	-1	-1	-1	1	1	-1	-1	1	1	1
3	1	-1	1	1	-1	-1	-1	1	1	-1	1	1	1	-1
4	1	-1	1	1	-1	-1	-1	1	1	-1	-1	-1	-1	-1
5	1	-1	2	-1	-1	-1	1	-1	-1	1	1	-1	1	-1
6	1	-1	2	-1	-1	-1	1	-1	-1	1	-1	1	-1	-1
7	1	-1	2	-1	-1	-1	1	-1	-1	1	1	1	-1	1
8	1	-1	2	-1	-1	-1	1	-1	-1	1	-1	-1	1	1
9	1	-1	3	1	-1	-1	-1	-1	1	1	-1	-1	-1	1
10	1	-1	3	1	-1	-1	-1	-1	1	1	1	1	1	1
11	1	-1	3	1	-1	-1	-1	-1	1	1	-1	1	1	-1
12	1	-1	3	1	-1	-1	-1	-1	1	1	1	-1	-1	-1
13	1	-1	4	-1	-1	-1	1	1	-1	-1	1	-1	1	-1
14	1	-1	4	-1	-1	-1	1	1	-1	-1	1	1	-1	-1
15	1	-1	4	-1	-1	-1	1	1	-1	-1	1	1	-1	1
16	1	-1	4	-1	-1	-1	1	1	-1	-1	1	-1	1	1
17	1	-1	5	1	1	1	1	1	-1	-1	1	-1	1	1
18	1	-1	5	1	1	1	1	1	-1	-1	1	-1	1	-1
19	1	-1	5	1	1	1	1	1	-1	-1	1	1	-1	-1
20	1	-1	5	1	1	1	1	1	-1	-1	-1	-1	1	-1
21	1	-1	6	-1	1	1	-1	-1	1	1	1	-1	-1	-1
22	1	-1	6	-1	1	1	-1	-1	1	1	-1	1	1	-1
23	1	-1	6	-1	1	1	-1	-1	1	1	1	1	1	1
24	1	-1	6	-1	1	1	-1	-1	1	1	-1	-1	-1	1
25	1	-1	7	1	1	1	1	-1	-1	1	-1	-1	1	1
26	1	-1	7	1	1	1	1	-1	-1	1	1	1	-1	1
27	1	-1	7	1	1	1	1	-1	-1	1	-1	1	-1	-1
28	1	-1	7	1	1	1	1	-1	-1	1	1	-1	1	-1
29	1	-1	8	-1	1	1	-1	1	1	-1	-1	-1	-1	-1

### JMP Custom Designer

Can we get a design in JMP with 64 subplots rather than the default 38? We can overwrite the Custom Designer default choices and ask the Custom Designer to generate a design with 8 Whole Plots and 64 Subplots as shown in Figure 10. The user needs to be aware then, that the “best” design may not be the default one offered by the Custom Designer.

Figure 10. Custom Design Inputs for  $2^1 \times 2^7 \times 2^8$  Experiment with 8 Whole Plots and 64 Subplots.

**Design Generation**

Hard to change factors can vary independently of Very Hard to change factors.

Number of Whole Plots

Number of Subplots

**Number of Runs:**

Minimum 137

Default 256

User Specified

The resulting JMP design is balanced and has the same structure as the PROC FACTEX one; i.e., 8 whole plots of size 8 each, and 64 subplots of size 4 each. However, all the main effects of this design are still confounded with long strings of 3-factor interactions as opposed to the FFS<sup>2</sup>P generated by PROC FACTEX. The generation of this design in JMP took over 50 minutes in an Intel® Core™ Duo CPU E6850 3GHz; 3GHz as compared to the 1 minute it took PROC FACTEX to find it.

### 5.2 A 4-STEP PROCESS EXAMPLE (SPLIT–SPLIT–SPLIT–PLOT)

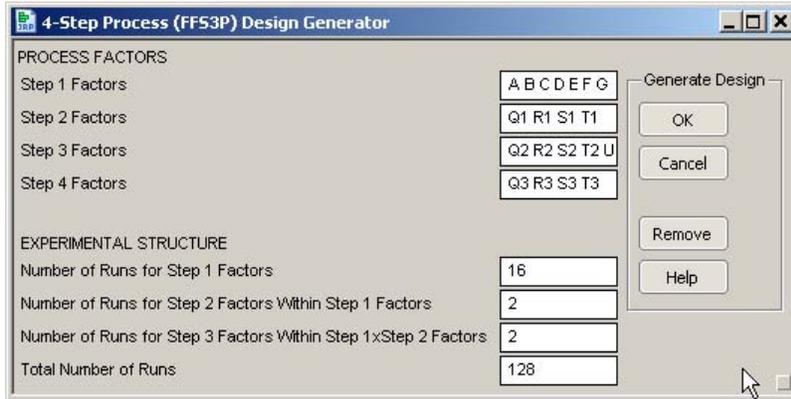
The product manufactured in this 4-Step example starts with the raw material at Step 1, where it gets processed using 7 factors: A B C D E F G. After Step 1, the output goes through 3 passes of a second process step. In the first pass 4 process factors are applied (Step 2): Q1 R1 S1 T1; in the second pass 5 factors (Step 3): Q2 R2 S2 T2 U; and in the third pass 4 factors (Step 4): Q3 R3 S3 T3. Even though the process has two steps but the second step is done three times giving rise to a “4-Step” process.

There are 20 process factors giving 20 main effects, and 190 two-factor interactions, for a total of 210+1 (mean) signals to be estimated. This requires at least 211 runs but due to the processing times this was thought to be too many. We wanted a design that will allow us to estimate all the 20 main effects clear from confounding with other 2-factor interactions, and as many 2-factor interactions clear from other 2-factor interactions was needed. The team decided that they could handle 128 runs.

Figure 11 shows the input window for the JMP-SAS application for generating a fractional factorial designs for this 4-Step process situation. As we the 3-Step situation we need to

1. Number of Runs for Step 1 Factors
2. Number of Runs for Step 2 Factors Within Step 1 Factors
3. Number of Runs for Step 3 Factors Within Step 1xStep 2 Factors
4. Total Number of Runs

**Figure 11. JMP Interface for Designing 4-Step Process Experiments.**



The inputs in Figure 11 indicate that we want to generate a 128-run design with 16 unique runs for the 7 Step 1 factors, 2 runs for the 4 Step 2 factors for each of the runs of the Step 1 factors, and 2 runs for the 5 Step 3 factors for each of the runs of the Step 1 and Step 2 factors ( $16 \times 2 \times 2 \times 2 = 128$ ). Figure 12 shows the partial JMP table with the design that was generated by PROC FACTEX.

**Figure 12. Partial JMP Table with Design for 4-Step Process Example.**

	Step1	A	B	C	D	E	F	G	Step2	Q1	R1	S1	T1	Step3
1	1	1	-1	-1	1	1	-1	-1	1	-1	1	1	1	1
2	1	1	-1	-1	1	1	-1	-1	1	-1	-1	1	1	1
3	1	1	-1	-1	1	1	-1	-1	1	-1	-1	1	1	2
4	1	1	-1	-1	1	1	-1	-1	1	-1	-1	1	1	2
5	1	1	-1	-1	1	1	-1	-1	2	1	1	-1	-1	1
6	1	1	-1	-1	1	1	-1	-1	2	1	1	-1	-1	1
7	1	1	-1	-1	1	1	-1	-1	2	1	1	-1	-1	2
8	1	1	-1	-1	1	1	-1	-1	2	1	1	-1	-1	2
9	2	1	-1	1	-1	-1	1	-1	1	-1	1	1	-1	1
10	2	1	-1	1	-1	-1	1	-1	1	-1	1	1	-1	1
11	2	1	-1	1	-1	-1	1	-1	1	-1	1	1	-1	2
12	2	1	-1	1	-1	-1	1	-1	1	-1	1	1	-1	2
13	2	1	-1	1	-1	-1	1	-1	2	1	-1	-1	1	1
14	2	1	-1	1	-1	-1	1	-1	2	1	-1	-1	1	1
15	2	1	-1	1	-1	-1	1	-1	2	1	-1	-1	1	2
16	2	1	-1	1	-1	-1	1	-1	2	1	-1	-1	1	2
17	3	-1	1	-1	-1	1	1	-1	1	-1	1	-1	1	1
18	3	-1	1	-1	-1	1	1	-1	1	-1	1	-1	1	1
19	3	-1	1	-1	-1	1	1	-1	1	-1	1	-1	1	2
20	3	-1	1	-1	-1	1	1	-1	1	-1	1	-1	1	2
21	3	-1	1	-1	-1	1	1	-1	2	1	-1	1	-1	1
22	3	-1	1	-1	-1	1	1	-1	2	1	-1	1	-1	1
23	3	-1	1	-1	-1	1	1	-1	2	1	-1	1	-1	2
24	3	-1	1	-1	-1	1	1	-1	2	1	-1	1	-1	2
25	4	-1	1	1	1	-1	-1	-1	1	-1	-1	-1	-1	1
26	4	-1	1	1	1	-1	-1	-1	1	-1	-1	-1	-1	1
27	4	-1	1	1	1	-1	-1	-1	1	-1	-1	-1	-1	2
28	4	-1	1	1	1	-1	-1	-1	1	-1	-1	-1	-1	2
29	4	-1	1	1	1	-1	-1	-1	2	1	-1	-1	-1	1

The above design is balanced, and it is only 0.01% of the total number of runs for the full factorial. This design has all the 20 main effects clear from confounding with 2-factor interactions, and allows us to estimate 104 out of the total 190 2-factor interactions, 70 of them clear from confounding with other 2-factor interactions. If needed, a follow experiments can be design to break the confounding of the statistically significant two-factor interactions.

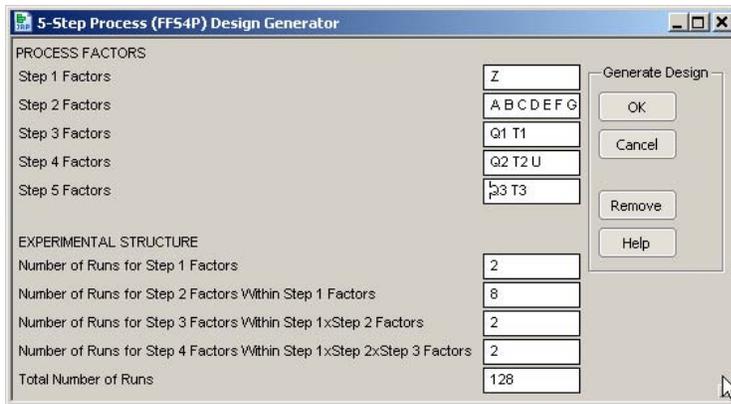
### 5.3 A 5-STEP PROCESS EXAMPLE (SPLIT-SPLIT-SPLIT-SPLIT-PLOT)

As a final example consider a 5-Step process with 15 factors distributed as follows:

- Step-1 Factors: Z
- Step-2 Factors: A B C D E F G
- Step-3 Factors: Q1 T1
- Step-4 Factors: Q2 T2 U
- Step-5 Factors: Q3 T3

We want to design a fractional factorial experiment in 128 runs that takes into account the 5 steps in the process, allowing for the restrictions in randomization between the 5 steps. Figure 13 shows the required inputs for the JMP-SAS FFS<sup>4</sup>P interface. The inputs in Figure 13 indicate that we want to generate a 128-run design with 2 unique runs for the Step 1 factor Z, 8 runs for the 7 Step 2 factors (A B C D E F G) for each of the runs of the Step 1 factor, 2 runs for the 2 Step 3 factors (Q1 T1) for each of the runs of the Step 1 and Step 2 factors, 2 runs for the 3 Step 4 factors (Q2 T2 U) for each of the runs of the Step 1 and Step 2 and Step 3 factors, and 2 runs for the 2 Step 5 factors (Q3 T3) for each of the runs of the Step 1 and Step 2 and Step 3 and Step 4 factors ( $2 \times 8 \times 2 \times 2 \times 2 = 128$ ).

Figure 13. JMP Interface for Designing 5-Step Process Experiments.



A partial view of the design is shown in Figure 14. This design has all 15 main effects clear from confounding with two-factor interactions, and allows us to estimate 66 out of the 105 2-factor interactions, with 43 of them clear from confounding with other 2-factor interactions.

Figure 14. JMP Table with Design for 5-Step Process Example.

	Step1	Z	Step2	A	B	C	D	E	F	G	Step3	Q1	T1	Step4	Q2
1	1	-1	1	1	1	1	-1	-1	-1	1	1	-1	-1	1	1
2	1	-1	1	1	1	1	-1	-1	-1	1	1	-1	-1	1	1
3	1	-1	1	1	1	1	-1	-1	-1	1	1	-1	-1	2	-1
4	1	-1	1	1	1	1	-1	-1	-1	1	1	-1	-1	2	-1
5	1	-1	1	1	1	1	-1	-1	-1	1	2	1	1	1	1
6	1	-1	1	1	1	1	-1	-1	-1	1	2	1	1	1	1
7	1	-1	1	1	1	1	-1	-1	-1	1	2	1	1	2	-1
8	1	-1	1	1	1	1	-1	-1	-1	1	2	1	1	2	-1
9	1	-1	2	1	-1	1	-1	1	1	-1	1	1	1	1	-1
10	1	-1	2	1	-1	1	-1	1	1	-1	1	1	1	1	-1
11	1	-1	2	1	-1	1	-1	1	1	-1	1	1	1	2	1
12	1	-1	2	1	-1	1	-1	1	1	-1	1	1	1	2	1
13	1	-1	2	1	-1	1	-1	1	1	-1	2	-1	-1	1	-1
14	1	-1	2	1	-1	1	-1	1	1	-1	2	-1	-1	1	-1
15	1	-1	2	1	-1	1	-1	1	1	-1	2	-1	-1	2	1
16	1	-1	2	1	-1	1	-1	1	1	-1	2	-1	-1	2	1
17	1	-1	3	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1
18	1	-1	3	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1
19	1	-1	3	-1	-1	-1	-1	-1	-1	-1	1	1	1	2	-1
20	1	-1	3	-1	-1	-1	-1	-1	-1	-1	1	1	1	2	-1
21	1	-1	3	-1	-1	-1	-1	-1	-1	-1	2	-1	-1	1	1
22	1	-1	3	-1	-1	-1	-1	-1	-1	-1	2	-1	-1	1	1
23	1	-1	3	-1	-1	-1	-1	-1	-1	-1	2	-1	-1	2	-1
24	1	-1	3	-1	-1	-1	-1	-1	-1	-1	2	-1	-1	2	-1
25	1	-1	4	-1	1	-1	-1	-1	1	1	1	-1	-1	1	-1
26	1	-1	4	-1	1	-1	-1	-1	1	1	1	-1	-1	1	-1
27	1	-1	4	-1	1	-1	-1	-1	1	1	1	-1	-1	2	1
28	1	-1	4	-1	1	-1	-1	-1	1	1	1	-1	-1	2	1

## CONCLUSION

The JMP Custom Designer is a powerful and flexible tool that allows users to design experiments that can take into account restrictions in randomization (up to three) and different types of factors (process and mixture). Designs that were impossible or difficult to design are now available through an easy-to-use interface. There are situations however, where a problem cannot either be solved by JMP's powerful design tools, more than 3 restrictions in randomization, or the design offered by JMP can be improved upon to better match the experimental situation. The good news is that by integrating the design tools available in JMP and the design tools available in SAS/QC, users are now able to use the most powerful design of experiments workbench available.

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